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Modelling and Multi-criteria Analysis of the Sustainability Dimensions for the Green Vehicle Routing Problem

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Abstract

The transport sector leads to detrimental effects on the economy, environment, and citizens quality of life. During recent years, some key-performance indicators have been proposed to quantify these negative impacts on the economic, environmental, and social dimensions of the sustainability concept. In this paper, we consider the sustainable vehicle routing problem that takes into account the aforementioned dimensions. We propose a multi-objective optimisation model to combine the three dimensions, as well as a biased-randomised iterated greedy algorithm to solve the integrated problem. A comprehensive set of experiments and a sensitivity analysis have been carried out with newly generated instances, which were adapted from existing vehicle routing benchmark instances. The sensitivity analysis is performed to measure the impact of each sustainability dimension and investigate trade-offs among them.

Keywords: Transportation, Sustainable vehicle routing problem, Multi-objective optimisation, Hybrid metaheuristic

1. Introduction

Many modern cities around the globe have to face increasing operational complexities as their population grow and new transport systems are considered, from bicycles to undergrounds and car sharing services (Faulin et al., 2019). This is partly due to the fact

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that an increase in population usually implies a higher level of mobility requirements, which leads to a boost in the expansion of e-commerce practices. Some of the transport-related challenges that society face include, depletion of natural resources, management of waste due to the increasing number of citizens, increase in road traffic accidents, and increase in traffic congestion and the associated levels of pollution. Consequently, Logistics and Transport (L&T) providers play a crucial role in the promotion of the sustainability concept in its different dimensions, including economic, environmental, and social (Browne et al., 2012). Therefore, L&T providers are faced with the challenge of managing their L&T operations while considering the economic, environmental, and social impacts. According to the report in the European Conference of Ministers of Transportation (ECMT Round Tables) (1999), a sustainable transport system is one that is safe, easily accessible, affordable, and environmentally friendly. This has resulted in an increase in research on Green VRPs (G-VRP) (Lin et al., 2014) usually connected with the Sustainable VRPs (SU-VRP) (Omidvar & Tavakkoli-Moghaddam, 2012), which is a much broader problem because it also includes other facets such as the social and the economic dimensions apart from the environmental dimension. However, in most sustainable VRP literature, the main objective is to minimise GHG emissions and in some cases, some economic costs (Erdoğan & Miller-Hooks, 2012; Schneider et al., 2014; Zhou et al., 2020). Mahdinia et al. (2018) stated that for a transport system to be regarded as sustainable, its social impacts must not be ignored. In this regard, road safety in relation to traffic accidents is considered as one of the most critical social indicators in road transport, which could be related to infrastructure and driver fatigue in relation to workload (Sharafi & Bashiri, 2016). Road traffic accidents have a direct and substantial effect on the residents of a city. For instance, accidents can cause pain, grief, and suffering to the casualty. According to the European Road Safety Observatory, over $4,800$ people were killed in collisions involving heavy vehicles in 23 EU countries in 2008 (European Transport Safety Council, 2011).

To the best of our knowledge, the existing SU-VRP literature (Toth & Vigo, 2014) lacks studies that holistically integrate the economic, environmental and social dimensions of sustainability in the context of road freight transport (Tang & Zhou, 2012; Vega-Mejía et al., 2019). Although the social dimension of transport is not straightforward to measure, it plays a relevant role in distribution activities related to retail and food shopping and delivery services (Eskandarpour et al., 2015; Faulin et al., 2005). In order to close these gaps, we propose a multi-objective optimisation model to model and measure the impacts and trade-offs of three sustainability dimensions for the SU-VRPs with high sensitivity towards the social and environmental impacts.

The costs studied in this work refer to cost of CO_2 emissions of conventional vehicles, fuel cost, drivers cost, vehicle fixed cost, and accident risk cost. Since accident risk costs are not easy to estimate, we select and implement some monetary values from Muñoz-Villamizar et al. (2017).The main contributions of this work are as follows: *(i)*

Develop a multi-objective optimisation model for the sustainable vehicle routing problem (SU-VRP), which integrates the economic, environmental, and social dimensions; *(ii)* Develop a hybrid solving method based on the combination of biased-randomisation (BR) techniques (Grasas et al., 2017) and an iterated greedy (IG) framework (Ruiz & Stützle, 2007); *(iii)* Provided a new set of benchmark instances for the SU-VRP, which are derived from well-known VRP instances; *(iv)* Conduct a comparative analysis of the performance of two multi-objective optimisation models, namely: the weighted sum model and the ϵ-constraint model; and *(v)* Perform a sensitivity analysis to evaluate the impacts and trade-offs between the sustainability dimensions. These contributions give insights into current L&T challenges.

The rest of this paper is structured as follows. In section 2, a literature review is presented. Section 3 provides a formal description of the problem addressed, including the multi-objective optimisation model. The proposed solving approach is presented in section 4. Computational results and their corresponding discussions are provided in section 5. Finally, section 6 presents the main conclusions and identifies future work directions.

2. Literature review on Sustainable Vehicle Routing Problem

Nowadays, the paradigm of smart and sustainable cities (Beneicke et al., 2019) proposes initiatives to reduce the negative environmental externalities resulting from the L&T activity, such as the use of light goods vehicles and electric or hybrid-electric vehicles (Erdoğan & Miller-Hooks, 2012; Juan et al., 2016) while optimising delivery routes to local stores or e-commerce users. In recent years, VRP studies have emerged that consider the environmental objective alongside the economic one. These studies generally aim to reduce GHG emissions and sometimes, some economic costs (Lin et al., 2014). However, in practice, a sustainable transportation system is one that is safe, easily accessible, affordable and environmentally friendly (McKinnon et al., 2015) and according to Dekker et al. (2012), there is the need for new modelling schemes in order to succeed in greening logistics operations. Among these new modelling concepts are the G-VRPs. The G-VRP takes into account wider operational objectives regarding GHG emissions minimisation which makes the problem more complex when compared to classical VRPs. The use of electric vehicles concept is gaining popularity as an effective way to significantly reduce emissions and energy consumption at the roadside thereby increasing environmental sustainability. In this regard, some researchers have proposed the use of Alternative Fuel Vehicles (AFVs) (Erdoğan & Miller-Hooks, 2012). However, AFVs have some limitations, such as limited driving ranges and limited refuelling stations (Erdoğan & Miller-Hooks, 2012; Pelletier et al., 2016; Eskandarpour et al., 2019; Hatami et al., 2020).

In Montoya-Torres et al. (2016) a G-VRP is solved with a heuristic that stores a set of routes defined by a randomised route-first cluster-second heuristics and a set partitioning formulation in the columns. Sawik et al. (2017) solved the G-VRP with multiple objectives, including both monetary and environmental. In Leggieri & Haouari (2017) an analysis of the distribution activity considering a given set of customers, a set of refuelling stations and eco-friendly vehicles is presented. The authors proposed a Mixed Integer Linear Programming (MILP) formulation for solving the G-VRP that minimises the total travelling distance. This formulation compacts many variables and constraints to design routes for a homogeneous vehicle fleet. The authors claim that the method is flexible enough to deal with any VRP problem with eco-friendly vehicles. The solution method is designed to optimally solve the G-VRP instances with 20 nodes and up to 10 refuelling stations. Similarly, Andelmin & Bartolini (2017) solved the G-VRP as a set partitioning problem to serve a set of scattered customers with eco-friendly vehicles. The authors demonstrated the advantages of partitioning formulation to solve instances with up to 110 nodes and 28 refuelling stations. Andelmin & Bartolini (2019) analysed the G-VRP considering refuelling operations between two nodes. The authors proposed a multi-start local search heuristic to generate a pool of routes. Finally, a partitioning method optimally combines these routes to determine the best solution. Based on 52 benchmark instances from the literature, the solution approach found 8 new best-known solutions and matched 43 solutions. Later Bruglieri et al. (2019a) proposed a path-based approach to generate feasible routes that serve a set of customers without intermediate refuelling stops. The solution method consists of a MILP and a heuristic to solve small and medium instances, respectively. The authors affirm that their solution approach outperforms the exact methods known in the literature. Bruglieri et al. (2019b) studied the G-VRP with time windows and Alternative Fuel Stations (AFSs).In their work, the authors considered that the AFSs capacity is such that queues at AFSs increase the refuelling time. The authors proposed two MILP formulations, one based on arc-variables and one on path-variables. The first models the capacity constraints by considering clone nodes (dummy copies) of the AFS for each fuelling operation by which the maximum number of refuelling necessary per route can be computed. The second model solves the problem through the combination of routes without intermediate stops at AFSs, thereby determining routes that link to the depot and the ones that connect the AFS. These routes are combined to determine the best solution. To this end, Macrina et al. (2019) analysed the G-VRP to serve all the customers satisfying the time window constraints, minimising the transportation and the recharging costs. Furthermore, the authors proposed an energy consumption model for a mixed fleet of electric and conventional vehicles. They demonstrated that energy consumption is underestimated in models that only consider travelling distance. Another recent study developed by Yu et al. (2019) addressed a multi-objective ride-sharing problem, similar to the dial-a-ride problem. There, carbon emissions are minimised while maximizing the ride profit. They affirmed that the distribution plan changes according to preferences and objectives of decision-makers.

The work of Bektaş & Laporte (2011) is considered as a landmark in the Pollution-

Routing Problem (PRP) literature, which considered as a category of G-VRP (Lin et al., 2014) where vehicle operating costs and emissions costs are jointly minimised. The authors presented a non-linear mixed-integer mathematical model of the problem with fixed speeds and an emission function based on Barth et al. (2005), but only solved small-size instances to optimality. An extension of this model was presented in Demir et al. (2012), where the authors allowed the use of lower speed with a non-decreasing discretised speed function and solved large-size problem instances. The advantage of using multiple vehicle types includes a reduction in fleet use, which means a reduction in economic and environmental costs. Koç et al. (2014) proposed an extension of the PRP to consider mixed fleet. According to these authors, this is the first paper that jointly investigates a heterogeneous VRP with time windows and the PRP objectives. Demir et al. (2014) extended the PRP to a bi-objective optimisation problem. The main argument of this work is that the objective of minimising fuel cost and driver time is conflicting. Therefore, they proposed to solve the problem considering the two objectives in parallel. Demir et al. (2014) extended the PRP to a bi-objective optimisation problem. The main argument of this work is that the objective of minimising fuel cost and driver time is conflicting. Therefore, they proposed to solve the problem considering the two objectives in parallel. In Kramer et al. (2015), the PRP is solved by means of a method combining a local search-based metaheuristics with integer programming and a speed-optimisation algorithm. For an extensive review on the G-VRP and PRP literature, readers can refer to Bektaş & Laporte (2011); Dabia et al. (2016); Tajik et al. (2014); Demir et al. (2015); Soysal et al. (2015); Zhang et al. (2015).

While environmental and economic objectives have been extensively studied in the SU-VRP literature, social objectives have received less attention (McKinnon et al., 2015). Indeed, it constitutes a subjective and complex component, where indicators may be based on a customer-employee perspective (Delucchi & McCubbin, 2010). Moreover, Bouchery et al. (2016) pointed out that models capturing the people element are scarce, which may be due to the difficulty of measuring such impacts. In this regard, Sharafi & Bashiri (2016) presented two mixed-integer programming models to tackle the economic and social aspects related to workload balance and its influence on the accident risk rate. The single objective model proposed in the study aims to maximise driver fairness and minimise accident risk by achieving a tour balancing objective. This is formulated as the minimisation of the gap between the longest tour and the shortest tour of AFVs. Two closely related works to the problem studied in this paper –in terms of the social dimension– are Eguia et al. (2013) and Sharafi & Bashiri (2016). In the latter, a genetic algorithm-based approach is applied to address large problem instances and the authors suggested that, it is essential to have a driver workload balance in order to minimise potential accident risk. In the former, the authors propose a single objective model to minimise internal costs, which are related to vehicle fixed and variable costs and external costs composed of noise pollution, air pollution, accident risk costs, and climate change costs. Despite proven relevance of sustainability impacts of L&T activities, only a small number of articles consider all three sustainability dimensions (economic, environmental, and social) as one decision criterion in the transport problem (Vega-Mejía et al., 2019). Additionally, only a few papers are focused on the trade-offs among these dimensions. As a result, the research proposed in this paper contributes to close this gap by developing a weighted multi-objective model that combines the three sustainability dimensions.

3. Problem definition and multi-objective optimisation model

In this section, we describe the proposed multi-objective SU-VRP optimisation models; a weighted sum model and an ϵ-constraint model. The proposed multi-objective optimisation models extend the existing sustainable VRP models by including vehicle operation costs, carbon emission cost, and safety cost. These costs are important for ensuring sustainability in transportation activities, especially when considering a coordination between the economic, environmental, and social dimensions.

The SU-VRP is defined over a complete graph $G = (N, A)$, where $N = \{0\} \cup N_c$ is a set of nodes, 0 corresponds to the depot, and $N_c = \{1, 2, \ldots, n\}$ to the customers. $A = \{(i, j) : i, j \in N, i \neq j\}$ is the set of arcs that connect all nodes in N. Each customer $i \in N_c$ has a known demand $q_i > 0$, while the depot is assumed to have a demand of zero. There is a fleet $K = \{1, 2, \ldots, \kappa\}$ of identical vehicles with a capacity $Q > 0$. $d_{ij} \geq 0$ and $t_{ij} \geq 0$ are the distance and travelling time between i and j. The vehicles start their trip at the depot, and return to it at the end of the trip. All customers' demands must be satisfied. The solution to this problem is a set of routes that can be represented by the binary variable x_{ijk}, *i.e.* $x_{ijk} = 1$ if a vehicle k, travels between nodes i and j and $x_{ijk} = 0$ otherwise. Each vehicle emits a certain amount of CO_2 emissions. In addition, there is a risk related to traffic accidents, which represents the social impact dimension and depends on the travelling distance between nodes i and j. Table 1 describes the notations for the sets, parameters, and variables of the multi-objective optimisation problem and the integer linear programming formulation for the SU-VRP is presented below.

Equation (1) represents the *economic dimension*, where z_1 is the total cost, which is composed of three types of costs. The first part is the fixed cost (FC), which includes depreciation, repairing, and maintenance of vehicles. The second, is a variable cost (DW) representing the driver wages, which depends on the total travelling time of routes. Finally, f_{ijk} computes the fuel consumption weighted by the fuel cost (C_f).

$$z_1 = \sum_{j \in N_c} \sum_{k \in K} FC \cdot x_{0jk} + \sum_{(i,j) \in A} \sum_{k \in K} DW \cdot t_{ij} \cdot x_{ijk} + \sum_{(i,j) \in A} \sum_{k \in K} C_f \cdot f_{ijk} \tag{1}$$

In Equation (3), the fuel consumption f_{ij} is a simplified version of the one proposed in Kuo (2010) and Zhang et al. (2015), where lph_{ij} is the fuel consumption per unit of time

Table 1: Model sets and parameters

Sets	
N	Set of all nodes
A	Set of arcs connecting nodes
N_c	Set of customers
K	Set of vehicles
S	Set of sustainability dimensions
i	Index of origin nodes
j	Index of destination nodes
k	Index of vehicles
s	Index of sustainability dimensions
Parameters	
q_i	Demand of node i
d_{ij}	Distance from i to j
t_{ij}	Travelling time from i to j
v_{ij}	Vehicle speed between i and j
Q	Maximum payload of a vehicle
DW	Driver cost per time unit
FC	Vehicle fixed cost
kpl	Km/l fuel consumption rate
lph	l/h fuel consumption rate
C_f	Fuel price per liter
C_e	Carbon price per kilogram CO_2
γ	Conversion factor for fuel consumption to CO_2 (kg-CO_2/liter)
α_s	Weight of the dimension s
Variables	
x_{ijk}	Binary variable: 1 if vehicle k traverses between nodes i and j, 0 otherwise
y_{ijk}	Integer variable: load on vehicle k on traversal between nodes i and j
f_{ijk}	Fuel consumption of vehicle k when travelling from i to j
f_{jk}	Continuous variable: remaining fuel of vehicle k when it arrives at node j
z_s	Continuous variable: impact on the dimension s
U_{jk}	Auxiliary variable to eliminate sub-tours

and kpl_{ij} in Equation (3) represents the fuel consumption per unit of distance (Muñoz-Villamizar et al., 2017). Thus, the fuel consumption of a vehicle per time unit when travelling from node i to j is given by:

$$lph_{ij} = \frac{v_{ij}}{kpl_{ij}} \tag{2}$$

Therefore, the fuel consumption of a loaded vehicle k when travelling from node i to j (f_{ijk}) follows the criterion proposed in Kuo (2010). We assume that an additional amount of load, with weight M, will increase fuel consumption by a ratio of p. Since in this study we do not consider pickup, only deliveries, the load in the vehicle only decreases as the vehicle delivers goods to the customers. Therefore, without loss of generality, we assume that making $p = 0$, then f_{ijk} can be up-bounded by f_{ij}, where the latter is given in Equation (3):

$$f_{ij} = lph_{ij} \cdot \frac{d_{ij}}{v_{ij}} \cdot \left(1 + p \cdot \frac{y_{ij}}{M}\right) \tag{3}$$

Similarly, Equation (4) computes z_2, which refers to the *environmental dimension*. This relates to the CO_2 emissions generated per unit of fuel consumed, where γ is an activity based emission factor (Piecyk et al., 2015). These emissions are monetised by the per unit emissions cost (C_e). This equation is a simplified version of that proposed by Kuo (2010) and Zhang et al. (2015).

$$z_2 = \sum_{(i,j)\in A} \sum_{k\in K} C_e \cdot f_{ij} \cdot x_{ij} \cdot \gamma \tag{4}$$

Finally, the *social dimension* (z_3) is computed by Equation (5), which estimates the cost of the accident risk for the travelling distance from customers i to j. This risk varies according to the travelling distance and the load of the vehicle k when travelling from customer i to j (Eguia et al., 2013), and a factor a proposed in Delucchi & McCubbin (2010) as a USD/kg-km coefficient used to monetise accidents.

$$z_3 = \sum_{(i,j)\in A} \sum_{k\in K} a \cdot d_{ij} \cdot y_{ijk} \tag{5}$$

The constraints of this problem are based on Erdoğan & Miller-Hooks (2012), these are:

$$\sum_{j\in N} \sum_{k\in K} x_{ijk} = 1 \qquad \forall\ i \in N_c \tag{6}$$

$$\sum_{i \in N} \sum_{k \in K} x_{ijk} = 1 \qquad \forall\, j \in N_c \tag{7}$$

$$\sum_{j \in N} x_{ijk} = \sum_{j \in N} x_{jik} \qquad \forall\, i \in N_c,\ k \in K \tag{8}$$

$$y_{ijk} \leq Q \qquad \forall\, (i,j) \in A, k \in K \tag{9}$$

$$\sum_{j \in N_c} x_{0jk} \leq 1 \qquad \forall\, k \in K \tag{10}$$

$$f_{jk} \leq f_{ik} - \frac{d_{ij}}{kpl} \cdot x_{ijk} + f_{0k} \cdot (1 - x_{ijk}) \qquad \forall\, i \in N, j \in N_c, k \in K \tag{11}$$

$$f_{jk} \geq \frac{d_{ij}}{kpl} \cdot x_{ijk} \qquad \forall\, i \in N, j \in N_c, k \in K \tag{12}$$

$$\sum_{i \in N} y_{jik} = \sum_{i \in N} y_{ijk} - \sum_{i \in N} q_j \cdot x_{jik} \qquad \forall\, j \in N_c, k \in K \tag{13}$$

$$y_{ijk} \leq (Q - q_i) \cdot x_{ijk} \qquad \forall\, (i,j) \in A, k \in K \tag{14}$$

$$y_{ijk} \geq q_j \cdot x_{ijk} \qquad \forall\, (i,j) \in A, k \in K \tag{15}$$

$$U_{ik} - U_{jk} + |N_c| \cdot x_{ijk} \leq |N_c| - 1 \qquad \forall\, i, j \in N_c, k \in K \tag{16}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall\, (i,j) \in A, k \in K \tag{17}$$

$$y_{ijk} \geq 0 \qquad \forall\, (i,j) \in A, k \in K \tag{18}$$

$$f_{ik} \geq 0 \qquad \forall\, i \in N, k \in K \tag{19}$$

$$U_{ik} \geq 0 \qquad \forall\, i \in N_c, k \in K \tag{20}$$

Thus, Equations (6) and (7) ensure that each customer is visited exactly once. The flow conservation is introduced by Equation (8). Moreover, Equation (9) guarantees that the total demand serviced by a vehicle does not exceed its capacity. Similarly, Equation (10) imposes that each vehicle can leave the depot at most once, while Equation (11) defines the state of a vehicle fuel amount after visiting a customer. Furthermore, Equation (12) guarantees that there will be enough remaining fuel to return to the depot from any customer location, while Equation (13) states that the load in the vehicle arriving at a customer j minus the demand of that customer equals to the load in the vehicle after serving it. Correspondingly, Equations (14) and (15) set lower and upper bounds for the load of vehicle k when travelling between i and j. Equally, Equation (16) avoids subtours, where U_{jk} is an auxiliary variable and $|N_c|$ is the number of customers. Finally, Equations (17) to (20) define variable domains.

3.1. A weighted objective function model

The proposed weighted objective function (z^*) in Equation (21) is defined as a holistic approach combining three sustainability dimensions by aggregating the objectives into a single objective with priority weights (Deb, 2014). This function aims to minimise the cost associated with the negative impacts on each dimension z_s, $\forall s \in \{1,2,3\}$. Likewise, α_s constitutes the weight or relative importance of the dimension s, where $0 \leq \alpha_s \leq 1$ and $\sum_{s=1}^{3} \alpha_s = 1$:

$$\text{Min } z^* = \alpha_1 z_1 + \alpha_2 z_2 + \alpha_3 z_3 \tag{21}$$

3.2. ϵ-constraint model

In the ϵ-constraint model, the multi-objective optimisation model is transformed into a single-objective model by transforming the other objectives into constraints and incorporating them in the constraint part of the model (Kovacs et al., 2015; Laumanns et al., 2006). The proposed ϵ-constraint objective function z_i in Equation (22) aims to minimise the cost associated with the negative impacts on each dimension z_s, $\forall s \in \{1,2,3\}$ in a lexicographic order, i.e.:

$$\text{Min } z_i \tag{22}$$

Subject to:

$$z_s - z_s^* \leq \epsilon_s \qquad \forall\ s \in \{1,2,3\} \setminus \{i\} \tag{23}$$

Objective function (22) minimises the three objective functions in lexicographic order: z_1 first, then z_2, and finally z_3. Constraint (23) is the constraint that bounds the objective value of z_s. The value of, ϵ_s accounts for the maximum deviation of epsilon constraint to its best value.

4. Biased-Randomised Iterated Greedy Local Search framework

We propose a Biased-Randomised Iterated Greedy with Local Search (BRIG-LS) approach to solve the SU-VRP. The BRIG-LS algorithm combines biased-randomised technique (Quintero-Araujo et al., 2017) with the iterated greedy (Ruiz & Stützle, 2007), which also includes a local search technique based on random swaps. The former methods have been selected because they constitute simple yet powerful techniques. Moreover, they use a reduced number of parameters, which makes it easier to replicate our experiments and also to apply our approach in real-life scenarios. The remainder of this section is split into the following subsections. The BRIG-LS generic framework, generation of solutions, the destruction-construction procedure, and the local search procedure.

4.1. BRIG-LS generic framework

The BRIG-LS (Algorithm 2) starts building an initial base solution (*baseSol*), which relies on the savings-based routing heuristics described in Dominguez et al. (2016). This solution is further improved by means of a local search. Then, it is stored as the best solution found so far (*bestSol*). Afterwards, an iterative processes is initiated with a stopping criterion based on the elapsed time (lines 5-20). Inside the iterative process, the base solution is destructed and re-constructed, and a local search is applied to the resulting new solution (*newSol*). The next step is to compute the relative percentage difference (*rpd*, line 8) between the costs of *newSol* and *baseSol*. If this measure is negative (*i.e.*, *newSol* is better), *newSol* replaces *baseSol*. In addition, it is checked whether *bestSol* should be updated. Oppositely, if *rpd* is positive, *newSol* may replace *baseSol* with a probability of e^{-rpd} (lines 15-18). This acceptance criterion was first proposed by Hatami et al. (2015), and is intended to avoid getting trapped in a local optimal. Finally, *bestSol* is returned.

Algorithm 1 :Pseudo code of the proposed IG-MMJ

```
1: procedure IG-MMJ(inputs, weights, maxTime, β, p)
                      ▹ inputs: transport network data , demands, Q, impact parameters
                      ▹ maxTime: max computing time allowed
                      ▹ p: parameter of the destruction stage
2:     baseSol ← double search(inputs, β)          ▹ Based on multi-criteria objectives
3:     bestSol ← baseSol
4:     while (stopping criterion is not met) do     ▹ Search for promising solutions
5:         newSol ← destructionConstruction(baseSol, p, inputs, β)
6:         newSol ← localSearch(newSol)
7:         rpd ← (cost(newSol) − cost(baseSol))/cost(baseSol) · 100
8:         if (rpd ≤ 0) then
9:             baseSol ← newSol
10:            if (cost(newSol) < cost(bestSol)) then
11:                bestSol ← newSol
12:            end if
13:        else                                     ▹ Avoid local optimal
14:            u ← generateU()
15:            if (u < exp(−rpd)) then
16:                baseSol ← newSol
17:            end if
18:        end if
19:    end while
20:    return bestSol
21: end procedure
```

Algorithm 2 BRIG-LS for SU-VRP

```
procedure BRIG-LS(inputs, weights, maxTime, β, p)
                    ▷ inputs: geographical coordinates, demands, Q, impact parameters
                    ▷ maxTime: max computing time allowed
                    ▷ β: parameter for biased randomisation
                    ▷ p: parameter of the destruction stage
    baseSol ← BR-CWS(inputs, β)                              ▷ Based on 'rich' savings
    baseSol ← localSearch(baseSol)
    bestSol ← baseSol
    while (stopping criterion is not met) do                 ▷ Search for promising solutions
        newSol ← destructionConstruction(baseSol, p, inputs, β)
        newSol ← localSearch(newSol)
        rpd ← (cost(newSol) − cost(baseSol))/cost(baseSol) · 100
        if (rpd ≤ 0) then
            baseSol ← newSol
            if (cost(newSol) < cost(bestSol)) then
                bestSol ← newSol
            end if
        else                                                 ▷ Avoid local optimal
            u ← generateU()
            if (u < exp(−rpd)) then
                baseSol ← newSol
            end if
        end if
    end while
    return bestSol
end procedure
```

4.2. Generation of solutions

The generation of the initial solution and the re-construction of the solutions, rely on the Biased Randomised (BR) heuristic. BR heuristic is built on the concept of 'savings'. This heuristic starts with a 'dummy' solution, where a vehicle has to visit only one customer and return to depot until all the customers have been visited. A savings list is stored which is computed following the process below.

- Two customers are merged in a vehicle and for each pair of customers, there is an associated savings resulting from visiting these customers together.
- The next step is to sort the savings in descending order, from the highest saving to the lowest one.
- The list is then traversed iteratively, applying feasible merges to generate a feasible solution.

The classic savings heuristic is deterministic, however, the novelty of BR heuristic relies in the introduction of randomness in the savings arrangement. This is done by assigning a given probability of being selected to each potential merge. The higher the saving, the higher the assigned probability. Typically, an empirical distribution such as the geometric one (with a parameter β) is employed to assign the probability (Grasas et al., 2017). Thus, this enhanced procedure allows us to get a potentially different solution at each run and, as a consequence, to explore a more extensive and promising search space. In both the classic savings heuristic and the randomised heuristic proposed by Grasas et al. (2017), savings are based on distances. In contrast, we propose a richer 'sustainable' savings function, considering route operation costs, CO_2 emissions costs, and accident risk costs.

4.3. Destruction-Construction procedure

This procedure (Algorithm 3) starts removing a p percentage of routes from a solution. As a result, we get the remaining routes (*partialSol*) and a list of unserved customers (*nodeList*). The construction stage applies the BR routing algorithm for these customers, which results in new routes. Finally, a new solution combining the existing and the new routes is returned.

Algorithm 3 Destruction and Construction Procedure

procedure DestructionConstruction($sol, p, inputs, \beta$)
  $partialSol \leftarrow$ removeRoutes(sol, p)
  $nodeList \leftarrow$ getFreeNodes($sol, partialSol$)
  $subSol \leftarrow$ BR-CWS($nodeList, inputs, \beta$)
  $newSol \leftarrow$ add($subSol, partialSol$)
  return $newSol$
end procedure

4.4. Local search procedure

Algorithm 4 describes the local search used, which is based on random swaps. This process is repeated iteratively until the following two conditions are met: *(i)* the number of trials is greater than the number of routes; and *(ii)* the last swap did not lead to an improvement. For each iteration of the loop, a route (*route*), and two different nodes ($node1, node2$) of this route are randomly selected. Then, a potential swap is assessed. The solution introduces this change if the cost is improved.

5. Computational experiments

The proposed optimisation models and BRIG-LS approach have been implemented on a standard personal computer as a Java application. In particular, an Intel QuadCore $i5$ CPU at 3.2 GHz and 4 GB RAM has been employed to execute all tests. The aim of the experiments are as follows: *(i)* Evaluate the performance of the optimisation models the

Algorithm 4 Local Search Procedure

```
procedure localSearch(solution)
    improvement ← TRUE
    numTrials ← 0
    while (improvement is TRUE or numTrials <numRoutes(sol)) do
        route ← getRandomRoute(solution)
        node1 ← getRandomNode(route)
        node2 ← getRandomNode(route)
        while (node1 is equal node2) do
            node2 ← getRandomNode(route)
        end while
        newRoute ← swap(route, node1, node2)
        if (cost(newRoute) < cost(route)) then
            improvement ← TRUE
            solution ← update(solution, newRoute, route)
        end if
        numTrials ← numTrials + 1
    end while
    return newSol
end procedure
```

and BRIG-LS algorithm in terms of solution quality against the best-known solutions (BKS) in the VRP literature; *(ii)*; Compare the performance of the weighted sum model (WM) and the ϵ-constraint model (ECM); and *(iii)* Conduct a sensitivity analysis using different weights on the sustainability dimensions to measure the trade-offs between the dimensions. Regarding ECM and WM, we use BRIG-LS to find a set of non-dominated solutions. For ECM, we convert the other objectives into constraints by imposing an upper bound ϵ. At first, the range of the objective functions z_i, $i = 1, 2, 3$ is determined using lexicographic optimisation. Then, each Pareto solution is generated within the ranges by ECM. For WM, the objective is to minimise the sum of the weighted objective function where α_s is set to 1 for each dimension. Table 2 presents the algorithm parameters used for all the computational experiments.

Table 2: Parameters of the algorithm.

Parameter	Value
$maxTime$	100 sec
Number of seeds	5
β	U(0.7,0.8)
p	U(0,100)
ϵ	U(0.01,0.10)

The run-time limit has been set to 100 seconds, which seems a reasonable time. We used 10 runs (each with a different seed for the pseudo-random number generator), and only the best results are stored. The distributions of β and p have been set after running a few experiments, based on the methodology described in Calvet et al. (2016). These parameters take stochastic values following the aforementioned distributions (β and p). The remainder of this section describes the SU-VRP instances, the assessment of the performance of the proposed BRIG-LS and the best known solutions in the literature and the numerical results of the computational experiments.

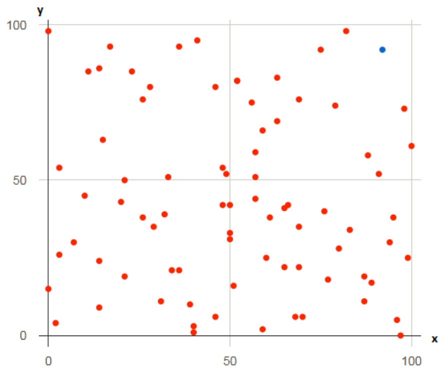
5.1. SU-VRP instances

To the best of our knowledge, there are no benchmark instances for the SU-VRP with three sustainability dimensions. The only benchmark similar to this work with 5 instances is due to Reyes-Rubiano et al. (2017). Therefore, we propose and consider a wider range of instances by adapting VRP instances from the literature `http://vrp.atd-lab.inf.puc-rio.br/index.php/en/`. We selected 43 classical VRP instances from Augerat et al. (1995) based on the following criteria: *(i)* instances for which the optimal solution is known; and *(ii)* instances with coordinates generated randomly within a square of side 100, in order to ensure feasible solutions when considering travelling times. The number of nodes ranges from 31 to 80. Figure 1 describes four types of instances belonging to sets A and B. Customers in set A are randomly located, and the depot may be in an outlying spot or in an intermediate spot (Figure 1(a)).In set B, the customers are clustered, and the depot is among clusters or outside (Figure 1(b)). Clustered instances are characterised as a set of clusters that integrate a number of nodes. In a cluster, the nodes have a distance measure similar to each other. Then, the solution for this kind of instances is defined by the insertion of nodes considering the vehicle payload. Similarly, the routes are limited by a maximum travelling distance. For the solution design, the customers' demand could be the most important item because of its variability in the cluster. In instances with randomly located customers, the distance and demand provide more flexibility in the search process of a solution.

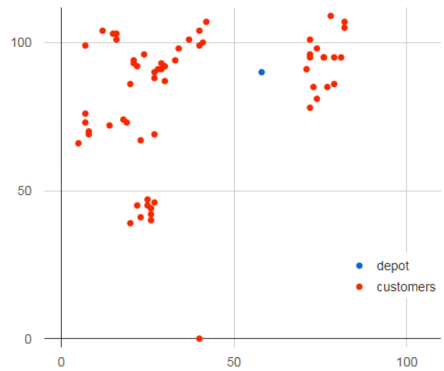
Travelling times are simulated by generating speeds. As suggested by Zhang et al. (2015), three speed levels are considered: high, moderate, and low. While high speed can be viewed as the transportation speed on a freeway, low speed may be related to urban transportation speed, and moderate speed represents an intermediate case. A uniform probability distribution is associated with each speed type. This is achieved by using the following parameters for each uniform distribution: $(90, 110)$, $(50, 70)$, and $(25, 45)$ (km/h), respectively. We set the speed of a vehicle as the mean speed assuming the following proportions of vehicles driving at a high, moderate, and low speed: 20%, 20%, and 60%, respectively.

Table 3 gathers the parameters needed to quantify the impacts, including units and references. The percentage gap for the experiments is computed as:

$$\%Gap = \frac{Tc - Tc^*}{Tc^*} \times 100.$$



(a) Set A. Depot in an outlying spot.



(b) Set B. Depot in an intermediate spot.

Figure 1: Different network configurations in sets A and B.

Table 3: Parameters that quantify and monetise impacts.

Input	Value	Converted to	Reference
kpl	0.052/km		Muñoz-Villamizar et al. (2017)
γ	0.75 kg of CO_2/l (rigid ≥ 7.5t - 17t)		Piecyk et al. (2015)
DW	0.0022 £/s	9.91 €/h	Koç et al. (2014)
FC	59.90 £/day	67.62 €/day	
C_f	1.4 £/l	1.58 €/l	
C_e	22 USD/ton of CO_2	0.02 €/kg of CO_2	Kossoy, Alexandre and Peszko, Grzegorz and Oppermann, Klaus and Prytz, Nicolai and Klein, Noemie and Blok, Kornelis and Lam, Long and Wong, Lindee and Borkent, Bram (2015)
a	[0.1-2] USD/ton-mile	0.0005 €/kg-km	Delucchi & McCubbin (2010)

Tc is the average solution obtained by BRIG-LS, and Tc^* is the value of the Best Known Solutions (BKS).

5.2. *Performance evaluation of BRIG-LS*

In order to validate the performance of BRIG-LS, we tested 40 instances with a distance minimisation objective. Firstly, the solutions provided by BRIG-LS are compared against the BKS from the literature. This comparison is conducted to evaluate the performance of the BRIG-LS approach on classical VRP instances with symmetric distances, and, also, to investigate the efficiency of the best solutions found by our metaheuristic against BKS in the literature. The results are summarised in Table 4. The first column shows the instance name, BKS distance is shown in the second column, and the BRIG-LS best solutions are given in the third column. The CPU time of BRIG-LS and the percentage gaps between the solutions are presented in the last column. Regarding the best found solutions obtained by BRIG-LS, 31 out of 40 instances offer a gap lower than 1%. This means that some of our solutions are slightly worse than BKS. On the average, BRIG-LS achieves a gap of 0.69% when compared to BKS, and achieves the best solution in 36.47 seconds.

Table 4: Validation of the BRIG-LS with the BKS when minimising distance.

Instance	BKS (Km)	BRIG-LS (Km)	Run time (s.)	Gap (%)
A-n32-k5	784	787.08	6.02	0.39
A-n33-k5	661	662.11	0.11	0.17
A-n33-k6	742	742.69	65.69	0.09
A-n34-k5	778	780.94	0.08	0.38
A-n36-k5	799	809.71	56.39	1.34
A-n37-k5	669	672.47	0.22	0.52
A-n37-k6	949	950.85	0.51	0.19
A-n38-k5	730	733.95	0.96	0.54
A-n39-k5	822	828.99	8.16	0.85
A-n39-k6	831	833.20	1.91	0.26
A-n44-k6	937	938.18	0.40	0.13
A-n45-k6	944	957.88	6.55	1.47
A-n45-k7	1146	1146.91	15.30	0.08
A-n46-k7	914	917.72	35.73	0.41
A-n48-k7	1073	1074.34	1.26	0.12
A-n53-k7	1010	1012.33	76.45	0.23
A-n54-k7	1167	1171.68	15.80	0.40
A-n55-k9	1073	1074.96	1.68	0.18
A-n60-k9	1354	1360.59	31.67	0.49
A-n61-k9	1034	1047.74	4.74	1.33
A-n62-k8	1288	1319.59	90.29	2.45
A-n63-k9	1616	1622.14	199.99	0.38
A-n63-k10	1314	1319.93	76.60	0.45
A-n65-k9	1174	1190.52	3.74	1.41
A-n69-k9	1159	1179.76	86.61	1.79
B-n31-k5	672	676.09	2.36	0.61
B-n34-k5	788	789.84	5.06	0.23
B-n38-k6	805	807.88	38.35	0.36
B-n41-k6	829	833.66	26.54	0.56
B-n43-k6	742	746.98	0.10	0.67
B-n44-k7	909	914.96	21.71	0.66
B-n45-k5	751	753.96	0.43	0.39
B-n50-k7	741	744.23	0.25	0.44
B-n50-k8	1312	1324.61	99.59	0.96
B-n57-k9	1598	1609.26	98.65	0.70
B-n63-k10	1496	1507.59	95.06	0.77
B-n64-k9	861	869.08	6.04	0.94
B-n66-k9	1316	1329.21	98.79	1.00
B-n67-k10	1032	1044.46	85.40	1.21
B-n68-k9	1272	1298.70	93.52	2.10
Average			36.47	0.69

5.3. Comparative analysis of WM and ECM

For the purpose of the computational experiments, the weights for WM are simply translated as importance levels where for each dimension, solutions found when only one dimension is considered. This means, $\alpha = 1$ for the economic dimension, environmental dimension, or social dimension. For ECM, the ϵ values are set according to Table 2. To conduct a fair comparative analysis, ECM and WM are run for 100 seconds. A detailed description of the parameters for the algorithm are provided in Section 5.
Table 5 summarises the results obtained for all the 43 instances obtained with ECM. The first column shows the instance name, and for for each dimension, total costs and %gaps between ECM and WM are shown in the corresponding column under each dimension. According to Table 5, WM outperforms ECM for the economic and environmental solutions by 0.14% and 1.33%, respectively. Interestingly, the solutions provided by ECM outperform the WM solutions for the social dimension by 7.11%. This indicates that the social dimension is most sensitive to ECM as this also minimises the cost of the economic and environmental dimensions by constraining them. In terms of the computation time, the average CPU time for ECM when minimising the social dimension is 91 seconds while WM has an average time of 31 seconds. When minimising the economic dimension, ECM has an average CPU time of 29 seconds and 7 seconds for WM. As for the environmental dimension, ECM and WM find solutions in an average time of 46 seconds and 16 seconds, respectively. Overall, the results of the experiments indicate that WM and ECM are competitive. However, ECM is not suitable for the evaluation of the trade-offs between the three dimensions when considering different importance weights.

5.4. Weight sensitivity analysis

The sensitivity analysis is used to analyse the multi-objective optimisation model behaviour and trade-offs that can be obtained from the different conflicting decisions (Chen et al., 2010). Hence, we propose a weight sensitivity analysis to show the impacts and trade-offs between the sustainability dimensions. This could offer valuable information to make informed decisions that allow to improve the quality of the operations in terms of both costs and impacts. For the purpose of computational experiments, these weights are simply translated as importance levels. This simply means that an importance weight of 100% = 1.

5.4.1. Iterative optimised weight sensitivity analysis

We propose to carry out further weight sensitivity analysis in order to investigate the behaviour of the solution when we assign a combination of different weights to the dimensions. These weights are determined following an iterative process, where a different combination of weights is assessed in each experiment. According to Kadziński et al. (2017), some multi-objective optimisation approaches use random initial weights. In contrast, we propose the configurations described in Equations (24) and (25) to generate

Table 5: Total cost and %gaps between the ECM and WM for all 43 instances

Instance	Economic Dimension			Environmental Dimension			Social Dimension		
	Total Cost (a)	**Total Cost (b)**	**%gap (a)-(b)**	**Total Cost (a)**	**Total Cost (b)**	**%gap (a)-(b)**	**Total Cost (a)**	**Total Cost (b)**	**%gap (a)-(b)**
A-n32-k5	518.58	521.11	0.49	520.35	523.41	0.58	529.37	550.89	3.91
A-n33-k5	491.87	491.55	-0.07	492.60	493.56	0.19	566.31	590.35	4.07
A-n33-k6	578.18	577.06	-0.19	647.64	578.57	-11.94	583.28	661.73	11.86
A-n34-k5	519.32	519.54	0.04	519.35	520.43	0.21	598.11	599.09	0.16
A-n36-k5	528.30	526.65	-0.31	525.24	528.13	0.55	545.96	646.49	15.55
A-n37-k5	495.99	494.35	-0.33	495.70	498.34	0.53	579.22	510.38	-13.49
A-n37-k6	629.05	626.98	-0.33	695.85	626.37	-11.09	706.27	793.87	11.04
A-n38-k5	510.91	508.94	-0.39	580.63	510.97	-13.63	589.68	596.05	1.07
A-n39-k5	530.18	531.56	0.26	530.85	533.06	0.41	551.51	694.37	20.57
A-n39-k6	598.50	600.16	0.28	669.08	599.43	-11.62	676.65	700.86	3.45
A-n44-k6	627.25	624.76	-0.40	627.82	696.73	9.89	715.73	726.71	1.51
A-n45-k6	633.69	626.53	-1.14	697.54	697.65	0.02	699.75	736.78	5.03
A-n45-k7	744.27	740.56	-0.50	745.77	751.66	0.78	749.36	839.36	10.72
A-n46-k7	688.39	687.45	-0.14	697.53	688.20	-1.36	693.02	795.97	12.93
A-n48-k7	721.43	723.72	0.32	722.34	722.74	0.06	738.86	841.80	12.23
A-n53-k7	712.76	709.80	-0.42	711.69	710.46	-0.17	796.68	825.54	3.50
A-n54-k7	749.57	748.09	-0.20	750.68	746.67	-0.54	822.78	855.28	3.80
A-n55-k9	860.39	860.66	0.03	929.52	929.43	-0.01	873.93	1035.17	15.58
A-n60-k9	930.17	932.94	0.30	928.45	931.60	0.34	959.20	1143.73	16.13
A-n61-k9	860.11	858.55	-0.18	920.51	919.06	-0.16	1001.84	1254.73	20.16
A-n62-k8	846.83	845.98	-0.10	848.05	846.55	-0.18	871.54	960.24	9.24
A-n63-k10	986.26	985.71	-0.06	988.78	988.16	-0.06	1089.86	1081.57	-0.77
A-n63-k9	994.08	985.81	-0.84	1061.42	1060.68	-0.07	1066.49	1123.36	5.06
A-n64-k9	945.75	941.98	-0.40	1019.02	949.16	-7.36	1132.44	1106.40	-2.35
A-n65-k9	884.13	883.76	-0.04	955.04	956.19	0.12	974.34	986.43	1.23
A-n69-k9	883.22	883.23	0.00	880.05	880.84	0.09	958.70	981.64	2.34
A-n80-k10	1118.38	1111.50	-0.62	1113.65	1118.93	0.47	1140.96	1249.15	8.66
B-n31-k5	492.15	492.13	0.00	493.58	493.17	-0.08	502.19	588.08	14.61
B-n34-k5	518.84	520.07	0.24	523.71	524.18	0.09	521.73	693.45	24.76
B-n38-k6	593.39	593.39	0.00	595.09	593.81	-0.21	609.18	611.63	0.40
B-n41-k6	602.06	598.96	-0.52	599.34	601.84	0.41	609.07	684.68	11.04
B-n43-k6	581.83	580.02	-0.31	582.37	582.93	0.10	672.08	677.06	0.73
B-n44-k7	683.30	685.62	0.34	684.00	684.12	0.02	694.71	862.93	19.49
B-n45-k5	516.10	514.67	-0.28	581.91	583.19	0.22	589.97	595.66	0.96
B-n45-k6	564.17	565.79	0.29	640.17	641.34	0.18	717.43	731.56	1.93
B-n50-k7	645.10	645.91	0.13	645.75	647.05	0.20	660.44	738.89	10.62
B-n50-k8	849.93	848.57	-0.16	847.75	850.62	0.34	854.32	1047.62	18.45
B-n57-k9	986.64	984.89	-0.18	980.80	987.65	0.69	1000.61	1100.39	9.07
B-n63-k10	1034.39	1036.05	0.16	1104.85	1037.36	-6.51	1124.85	1142.42	1.54
B-n64-k9	813.51	811.66	-0.23	881.78	882.19	0.05	962.53	964.29	0.18
B-n66-k9	918.46	918.69	0.02	994.90	921.67	-7.94	996.65	1005.29	0.86
B-n67-k10	917.38	917.25	-0.01	929.45	927.26	-0.24	941.73	1010.84	6.84
B-n68-k9	915.27	910.13	-0.56	909.09	909.36	0.03	1001.75	1012.46	1.06
Average	726.05	724.95	-0.14	750.46	741.27	-1.32	783.05	845.47	7.11

Total cost (a): ECM total cost of minimising one dimension with the other dimensions as constraints; Total cost (b): WM total cost minimising the one dimension.

7 scenarios. In each iteration, the weights $(\alpha_1, \alpha_2, \alpha_3)$ may take different values, while the parameters θ and δ take random values in the range $[0, 1]$. We limit the experiment up to 100 seconds for each weight combination. $\alpha_1, \alpha_2, \alpha_3$ are the importance weights

for z_1, z_2 and z_3 respectively.

$$\alpha_1 = 50 + 10 \cdot \theta;\ \alpha_2 = 20 + 10 \cdot \theta;\ \alpha_3 = 30 - 20 \cdot \theta \tag{24}$$

$$\alpha_1 = 40 - 20 \cdot \delta;\ \alpha_2 = 10 + 20 \cdot \delta;\ \alpha_3 = 50 - 10 \cdot \delta \tag{25}$$

Table 6 provides the selected scenarios generated using Equations (24) and (25).

Table 6: Table of scenarios with weight combinations

Scenario	Weights (%)		
	α_1	α_2	α_3
S1	52.0	30.0	18.0
S2	53.4	23.2	23.2
S3	55.8	25.8	18.4
S4	47.2	19.2	33.5
S5	40.3	30.3	29.3
S6	22.9	34.9	42.2
S7	49.0	21.0	30.0

According to Table 6, most scenarios assign more importance to z_1 than the other dimensions. However, this does not mean that further experiments may not yield scenarios assigning greater importance to z_2 or z_3 as presented in Table 6. Nonetheless, for the sake of this research, we have kept the generated scenarios and discuss the findings based on these scenarios. Recall that z_1, z_2 and z_3 represent the economic, environmental, and social dimensions costs and z^* represents the total cost. Table 7 summarises the quality of the solutions under different scenarios. The first four columns represent the different scenarios and weights according to Table 6. Each row shows the scenario, the combination of weights assigned to the dimensions, and the cost obtained for each dimension with the assigned weight.

Figure 2 shows the solution behaviour with respect to total cost. The best economic cost achieved is reached when z_1 is assigned an importance weight of 40%, while there is a trade-off between the environmental and social costs. However, notice that the best environmental cost is found when z_1 is assigned an importance weight of 52%, while maintaining similar weight for z_2 and decreasing the importance weight of z_3. This behaviour may be attributed to the the fact that since z_1 is impacted by travelling distance and travelling time, higher weights amplify the effect on z_2 since it is also measured in the travelling distance. In contrast, the least social cost is found when z_3 is the most important in scenario $S6$. This can be attributed to the impact of the load factor in z_3. Also, notice that if z_3 is considered as the most important, this increases the impact on z_1 and leads to the overall most expensive solution. Hence, based on the above scenarios, it can be concluded that the lowest total cost we achieved is in scenario $S2$, where the

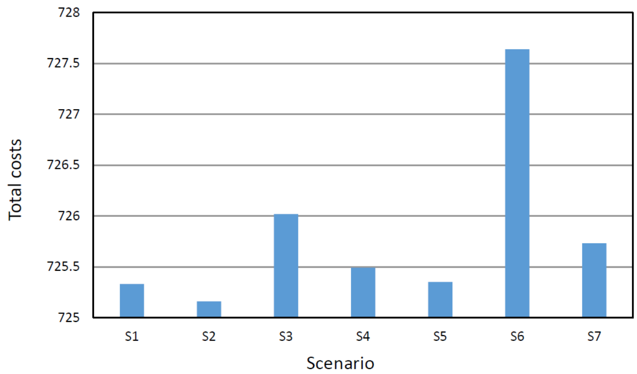


Figure 2: Average total cost for different scenarios.

importance weights are set to: α_1 = 53.4%, α_2= 23.2%, and α_3=23.2%. Certainly, the total cost increases when α_1 is higher or lower than 53.4%.

Table 7: Performance under different scenarios.

	Weights (%)			cost(€)			
Scenario	α_1	α_2	α_3	z_1	z_2	z_3	z^*
S1	52.0	30.0	18.0	687.32	15.29	22.72	725.33
S2	53.4	23.2	23.2	687.18	15.30	22.69	725.16
S3	55.8	25.8	18.4	687.66	15.33	23.03	726.02
S4	47.2	19.2	33.5	687.67	15.33	22.49	725.49
S5	40.3	30.3	29.3	687.13	15.28	22.94	725.35
S6	22.9	34.9	42.2	689.85	15.47	22.32	727.64
S7	49.0	21.0	30.0	687.84	15.33	22.56	725.73

Table 7 analyses the solutions for all tested instances and scenarios, a closer analysis of the performance of z_1, z_2, z_3, and z^* is shown in Figure 3, which uses instance A-n37-k6. In this instance, the customer nodes are randomly scattered within a square of side 100, and the depot is located in the bottom corner of the square.

Each polygon represents the solution for a scenario generated based on the preference weight assigned to each dimension. For the economic, environmental, and social solutions, a 100% importance weight is assigned separately. For the sustainable solution, we refer to scenario $S2$. The four angles of the plot represent the total cost and the cost of the dimensions that make up the total cost.

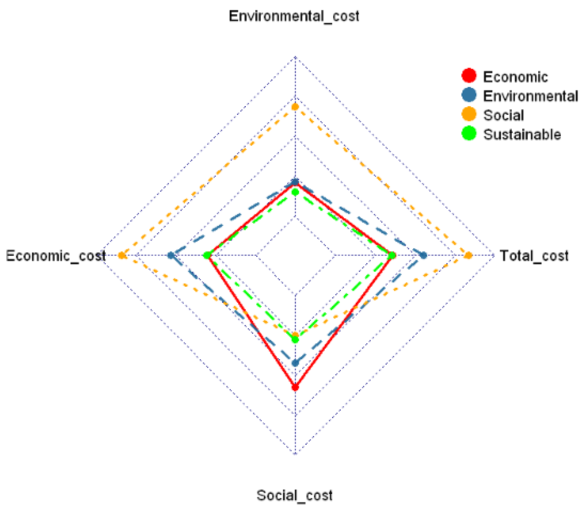


Figure 3: Radar plot comparing the performance of dimensions corresponding to the A-n37-k6 instance.

According to Figure 3, minimising the economic cost leads to an increase in the social and environmental costs. While the economic solution yields the lowest economic and environmental costs when compared to both the environmental and social solutions, it reaches the most expensive social cost. It can be observed that, overall, the sustainable solution reaches the lowest overall total cost.

In Figure 4, the average cost percentage for all instances, with respect to the total cost for each solution is presented. This also describes the trade-off between the cost of the different dimensions based on the previously described scenarios.

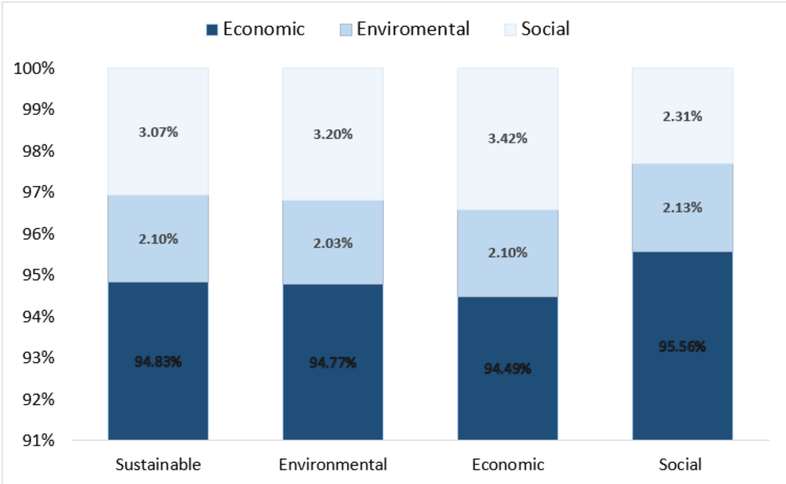


Figure 4: Average cost percentage according to economic, environmental and social dimensions.

For the sustainable solution, the economic, environmental, and social cost percentages are 94.83%, 2.10%, and 3.07%, respectively. However, when considering the economic solution, the economic, environmental, and social cost percentages are 94.77%, 2.03%, and 3.20%, respectively. Nevertheless, notice that the economic solution is less expensive in terms of the economic cost compared to the environmental and social solutions. In a similar manner, when the environmental or social dimensions costs are assigned a 100% importance, a trade-off can be observed between the economic, environmental, and social solutions. Also, notice that the social solution conflicts most sharply with the economic and environmental solutions, and the weight combination in scenario $S2$ may serve as a standard reference for the sustainability concerned decision-maker. In contrast, the decision-maker who is more profit chasing may use the weight combination in scenario $S5$ as a reference weight choice. For an environmentalist, the scenario $S1$ combination will be preferable as it softly trade-offs profitability and safety for environmental benefits. Lastly, for an accident risk-averse decision maker, scenario $S6$ may be the preferred weight choice, as it offers the cheapest accident risk cost, while being more expensive in terms of economic and environmental costs.

5.4.2. Practical weight sensitivity analysis

Although the weighted approach is typically applied for many multi-objective combinatorial optimisation problems, it is still not obvious how the weights should be selected. Nevertheless, some authors have proposed to use different weight selection methods. Thus, we have implemented the Practical Weight Sensitivity (PWS) method introduced by Jones (2011). This method allows the exploration of the whole weight space as many decision makers have a priority for some data besides their initial weighting estimate. A sensitivity analysis is performed for different importance weights on the sustainability dimensions proposed in the optimisation model.

By applying the PWS method in this paper, a set of 12 different scenarios with the weight combination (α_1,α_2,α_3) is generated to evaluate the performance of the proposed model. These weights represent the relative importance of each dimension in the weighted objective function (Equation 21). A three-dimensional weight space is generated in Figure 5 and Table 8 shows these weights.

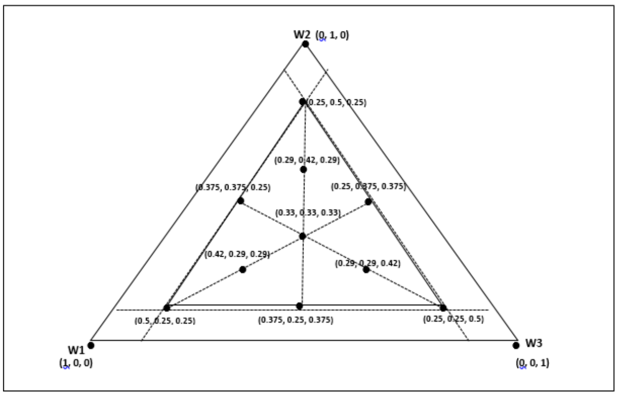


Figure 5: PWS 3*D* weight space.

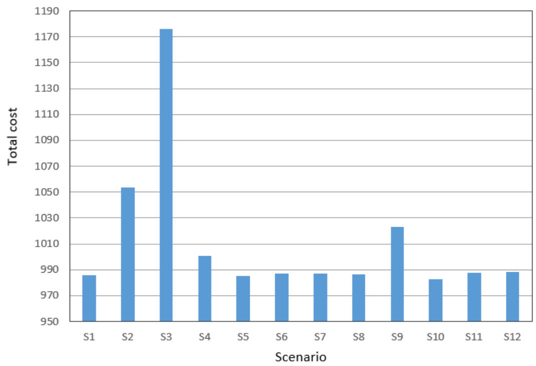
In this Table, the sets of weights are defined as scenarios which are represented by S_i, with $i \in \{1, 2, \ldots, 12\}$. The weights $(1, 0, 0)$, $(0, 1, 0)$, and $(0, 0, 1)$ are assigned in order to obtain the lower bounds for the cost of each dimension.

Table 8: Scenarios generated using the PWS method.

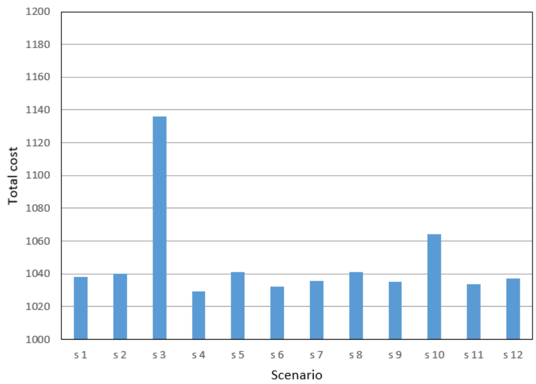
Scenario	Weights		
	α_1	α_2	α_3
S1	1.00	0.00	0.00
S2	0.00	1.00	0.00
S3	0.00	0.00	1.00
S4	0.33	0.33	0.33
S5	0.50	0.25	0.25
S6	0.25	0.50	0.25
S7	0.375	0.375	0.25
S8	0.25	0.375	0.375
S9	0.375	0.275	0.375
S10	0.42	0.29	0.29
S11	0.29	0.42	0.29
S12	0.29	0.29	0.42

In order to analyse the trade-offs between the cost of the dimensions, we evaluate the impact of the weight assigned to the cost of the dimensions on the overall total cost. Two large instances with different customer outlay (A-n63-k10 and B-n63-k10) have been selected. The reasons for the choice of these test instances are: *(i)* the node size and the number of available vehicles are the same; *(ii)* the outlay of nodes differs in both instances, which we presume may influence the behaviour of the solution.

The results of the experiments shown in Figure 6 are the average of 10 runs. Notice that minimising the total cost to obtain lower bounds for each dimension with a 100% importance, does not provide the cheapest solution, as can be seen from Figure 6 in scenarios $S1$, $S2$, and $S3$.



(a) A-n63-k10 scenarios total costs.



(b) B-n63-k10 scenarios total costs.

Figure 6: A-n63-k10 and B-n63-k10 total cost

On the one hand, for instance A-n63-k10 with a scattered outlay, scenario $S1$ provides a solution which is up to 0.04% more expensive than the solution provided by scenario $S5$. A similar behaviour can be observed for the solutions obtained in scenario $S2$ and scenario $S3$. Lastly, notice that scenario $S10$ provides the cheapest total cost with total cost saving of 0.24% in comparison to scenario $S5$. $S10$ scenario is when z_1, z_2 and z_3 are assigned α_1 = 42%, α_2 = 29%, and α_3 = 29%, respectively.

When the nodes are clustered in B-n63-k10, the weight assigned to the dimensions influences the overall cost. In this type of node configuration, the vehicle payload will have a strong impact on the assignment of nodes to routes. Despite this influence, the most expensive solution is provided in scenario $S3$, when z_3 is the most important, although it is important to highlight that this is load-related. Moreover, when z_1, z_2 and z_3 are given equal importance with α_1 = 33.33%, α_2 = 33.33%, and α_3 = 33.33%, this scenario achieves a cost-saving of 9.4%. This indicates that balancing between distance, travelling time, and load minimisation may lead to an overall cost saving, especially when nodes are clustered together.

6. Conclusions and future research

The primary goal of this paper is to contribute to the sustainable VRP literature by incorporating three key sustainability dimensions and the evaluation of the trade-offs among the dimensions. To the best of our knowledge, this is the first study that investigates the trade-off between these sustainability dimensions in the context of the VRP. We have developed a novel multi-objective optimisation model to integrate the three sustainability dimensions and a metaheuristic that hybridises a biased randomised savings heuristic and an iterated greedy local search method. The proposed hybrid metaheuristic extends the classic savings heuristic by building a probabilistic savings list based on the cost of three sustainability dimensions. The impacts of the three dimensions are measured in terms of vehicle distribution costs, CO_2 emissions costs, and accident risk costs. While the economic dimension is based on travelling distances and times, the environmental and social dimensions rely on carbon emissions based on travelling distance and risk of accidents, which are based on distance and vehicle load, respectively. We have conducted a comparative analysis to compare the performance of the weighted sum and the ϵ-constraint models. The performance of the models are compared when we optimise the cost of a single dimension. The computational results show that the weighted sum model outperforms the ϵ-constraint model in terms of the economic and environmental solutions. However, the ϵ-constraint model outperforms the weighted sum model in terms of the social solutions. The results provided by the weighted sum model are very competitive in terms of CPU time. A set of sensitivity analysis has been proposed and implemented for the weighted sum model. Computational experiments have found that considering all the three dimensions can offer savings of up to 0.4% of the total costs as opposed to considering only a single dimension. Additionally, we have observed that irrespective of the network configuration (scattered or clustered), the social dimension conflicts sharply with the economic and environmental dimensions. This proves the value of a multi-objective approach, since it shows the trade-offs between the three sustainability dimensions.

Several lines of future work are identified from this work. Firstly, the introduction of sustainability dimensions in richer vehicle routing problems can be explored (*e.g.*, considering electric vehicles and heterogeneous fleets). Similarly, uncertainty in real-life operations could be taken into account by modelling travelling times or customers' demands as stochastic variables. In addition, more research on social dimensions is needed. For instance, other social impacts of transport activity such as fairness and balanced routes may be considered. Likewise, more realistic formulations of policy-driven models that highlight the importance of considering the economic, environmental, and social sustainability dimensions are necessary for generating more practical insights and engaging stakeholders, which could lead to sustainability policy making.

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